The Thesis Committee for Neil Timothy Anderson
Certifies that this is the approved version of the following thesis:

An Analysis of the Effect of Mid-Season Trades on Team Performance in the National Basketball Association

APPROVED BY
SUPERVISING COMMITTEE:

Supervisor: _____
Janice S. Todd

_____
Emily S. Sparvero

An Analysis of the Effect of Mid-Season Trades on Team Performance in the National Basketball Association

by

Neil Timothy Anderson, B.S.Kin.Health

Thesis

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science in Kinesiology

The University of Texas at Austin

May 2016

Acknowledgements

First and foremost, I would like to thank Dr. Jan Todd and Dr. Emily Sparvero for helping me along the way with my thesis. Their guidance and feedback over the course of writing this thesis was greatly appreciated.

Additionally I would like to thank Dr. Martin Tombari for his help with some statistical questions. Additionally it was from his class I got the initial ideas that eventually came to be represented in this thesis.

Next I would like to thank Dr. Matt Bowers, Dr. Tolga Ozyurtcu, and Dr. Thomas Hunt for their guidance over the years during my education here at the University of Texas. Their support from my first days as a freshman to my final days as a graduate student has come to help shape the person I am and the work that I produce.

Finally, I would like to thank my family and friends for their support over the years, especially through the thesis writing process. They were always there for me for moral support or to listen to ideas and lend advice. Their support was probably one of the key contributors to my success.

Abstract

An Analysis of the Effect of Mid-Season Trades on Team Performance in the National Basketball Association

Neil Timothy Anderson, MSKin

The University of Texas at Austin, 2016

Supervisor: Janice S. Todd

One of the most important duties of a sports manager is ensuring a team keeps winning to the best of its ability. If a team is performing poorly, the manager will typically take action to try and remedy the situation, usually through coaching/administrative changes or player trades. The more we can understand how these actions affect a team's performance, the better we as managers can work to help our teams. Thus the purpose of this research was to gain a greater understanding of how mid-season player trades affect a team's performance. Using simple statistical testing over a five-year period encompassing the 2010-11 season to the 2014-15 season, data was collected from all thirty teams each season to determine rates of improvement, decline, or no change in team performance following a trade. Comparisons were also made between the teams that participated in a significant trade and those that did not. Of the forty-seven NBA teams that had a trade, four were determined to have improved following their trade while one team was found to have declined. Of the ninety-five NBA teams that did not meet the requirements for a trade, five were determined to have improved after the trade

deadline and five were determined to have declined. Overall, it was determined that there was no statistically significant difference in these rates of improvement, decline, or no change between the trade and non-trade teams. As such it seems that the only generalization that can be made about trading is that it likely will not affect team performance. Likewise, not trading typically will not affect team performance.

Table of Contents

List of Tables

List of Figures

Introduction

Professional sports offer an interesting environment in which to examine competitive advantage. Many precautions are taken by the different sports league's governing bodies in order to ensure a level playing field between the franchises. In the National Basketball Association (NBA), for example, the teams are subject to a salary cap, which prevents any one team from signing all of the best players. Additionally since players come from either a regulated draft system or the pool of free agents, all of the teams have the same resources when looking at player talent. Similarly, teams have access to all of the same coaches. Because of this, any attempt to gain a competitive advantage seems to come from how a franchise can utilize its resources better than others.

There are three groups within an NBA franchise that have an impact on the team performance and, thus, could be possible sources of competitive advantage. These are: the Management, the Coach, and the Players. Management has the largest organizational influence out of the three, as Management typically controls personnel decisions for the Coach and Players. The Coach has influence over the players, and changing out a coach with another one would be much more cost effective than changing players. However, many researchers have indicated that altering coaches may have a negligible, if not outright negative, impact on the team's performance. Finally there are the Players. They are the group directly impacting the team's performance, so it would seem logical that, if the team was performing poorly, changing out player personnel could potentially counteract this problem. However, it was shown by Berman, Down, and Hill (2002) that keeping a team together for a longer period of time causes an increase in tacit knowledge and team performance. Because of this, we enter a sort of "Manager's Dilemma" where immediate improvement is pitted against long-term improvement,

and selecting one virtually negates the other. If a trade takes place, it would stand to reason that the roster turnover would stymie the growth of the team tacit knowledge, especially if important players are traded. Conversely, committing to keeping a team together to improve tacit knowledge could mean giving up on any trades or roster changes that might help out more immediately.

As such, it needs to be more clearly understood how trading affects team performance, and if there is any generalizable outcome. Additionally, the impact of teams experiencing roster turnover needs to be compared to teams without roster turnover, to look at differences in performance. Hopefully this will help managers and owners gain insight into this problem of change-versus-retention and can possibly find if one is better than the other, or when it might be beneficial to commit to one strategy or the other.

As a manager of a basketball franchise, there are two groups to focus on to attempt to improve the team's competitive advantage: coaches and players. Current research tends to point towards a negative relationship between coach turnover and team performance, so it seems best to try to avoid changing coaches. This leaves players as the best option. However, what exactly do you do with the players? The manager could choose to focus on acquiring the best players possible via signings or trades, or, as Berman et al. (2002) have shown that retaining players for the long-term can increase a team's tacit knowledge and thus performance.

Literature Review

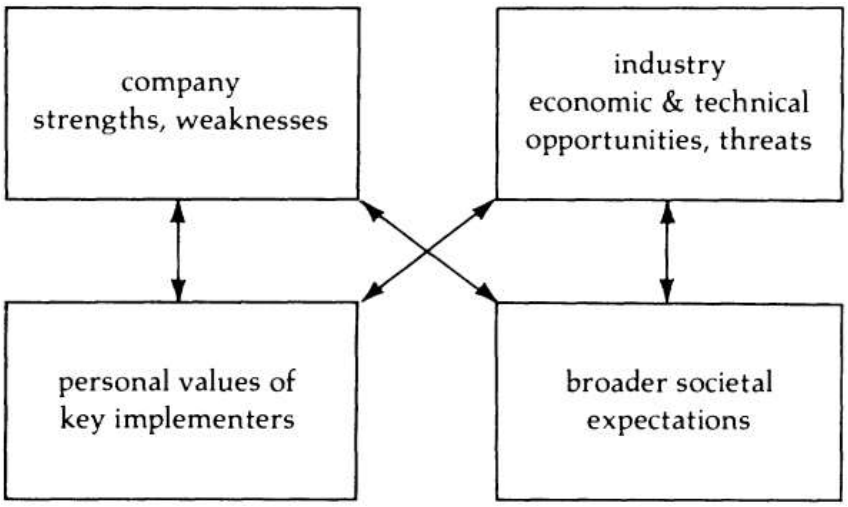
One of the most important concepts within business strategy is that of competitive advantage. Competitive advantage can be defined as the ability of a firm to implement a value creating strategy that is not also being implemented by any current or future competitor (Barney 1991).

Barney (1991) defines competitive advantage as the ability of a firm to implement a value creating strategy that is not also being implemented by any current or future competitor. This definition, however, requires further unpacking to fully understand. Hofer and Schendel (1978) claimed that strategy is the main link between a firm's goals and the plans and policies that guide its activities. They further define it as how the firm matches its internal resources and skills to the opportunities and risks of its external environment. They stress the importance of strategy in five areas as it (1) aids in the formulation of organizational goals and objectives, (2) aids in the identification of major strategic issues, (3) assists in the allocation of discretionary strategic resources, (4) guides and integrates the diverse administrative and operating activities of the organization, and (5) assists in the development and training of future general managers (pp. 5-6). According to Christensen, Andrews, and Bower (1978), corporate strategy is a process that is virtually inseparable from the structure, behavior, and culture of its company. They advise that strategy formulation should include identifying the opportunities and threats in the company's environment and before any choice can be made, the company's strengths and weaknesses need to be appraised together with the resources the company has available. Finally they go on to suggest that the determination of strategy also requires consideration of what alternatives the chief executive and their associates might prefer. They go as far as to say "[p]ersonal values, aspirations, and ideals do, and in [their] judgement quite properly should, influence the final

choice of purposes" (p. 129). Porter (1980) says that the goal of competitive strategy is for a business to find a position in its industry where it can best defend itself against the four competitive forces, or influence them to their favor. The four competitive forces being the threat of new entrants, the bargaining power of buyers, the threat of substitute products or services, the bargaining power of suppliers, and the rivalry among existing firms. Porter later goes on to warn that a firm that fails to create any strategy, even one of three generic strategies – cost leadership, differentiation, and focus – will end up being "stuck in the middle", causing the company to be in an extremely poor strategic situation (p. 41). However, Porter goes on to explain that each of the three generic strategies come with their own set of unique risks.

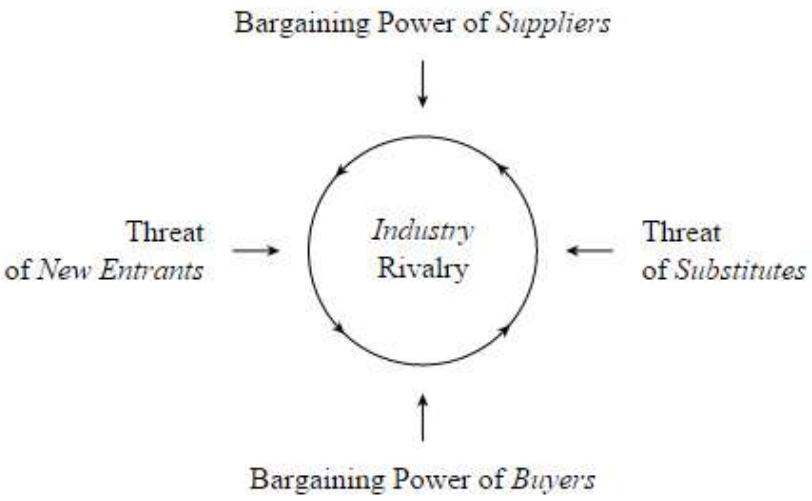
Thus, we can come to infer that a proper strategy will be a unique strategy that not only takes into account the firm's internal strengths and weaknesses and external opportunities and threats, but also takes into account the administration's personal opinions on the situation. Porter (1981) presents this form of the Learned, Christensen, Andrews, and Guth (LCAG) model as the four key elements of effective strategy formulation, seen below.

Figure 1: The Four Key Elements of Effective Strategy (source: Porter, 1981)



From here, we can return to the concept of competitive advantage. Porter (1985) suggests that competitive advantage comes from the value a firm is able to create for its buyers that exceeds its cost of creating it. Again this goes back to the ideals of cost leadership and differentiation. Using the Five Forces model a firm can look at its industry and find which of the factors are most important to their own and their industry's profitability. This model is shown below.

Figure 2: The Five Forces Model (Source: Porter 1985)



Lastly there is the concept of a sustained competitive advantage. This does not have to do with maintaining a competitive advantage over a given period of time. A sustained competitive advantage is one that manages to survive after any attempts to duplicate it have ceased (Barney, 1991). This does not mean that the advantage will last forever, merely that it will withstand any attempts to compete it away in the current competitive environment that the firm exists in.

Most professional sports, however, have been established in a manner that works to achieve parity. This competitive balance is needed to ensure the viability of the teams across the league, and efforts to achieve competitive balance are intended to prevent one team from achieving sustained competitive advantage (i.e., a dynasty). Humphreys (2002) makes a strong point of this, saying "If a league lacks competitive balance, fan interest in the weaker teams will fall, and eventually, fan interest in the stronger teams will also decline" (p. 133). As anyone one team gains player talent, thereby increasing their team performance, they cause all of the other teams in the league to equally decline in performance in a form of equivalent exchange, as the league average win percentage must always be at .500 (Késenne, 2000; Fort & Quirk, 1995). Thus, the leagues put into place various safeguards to work to create this balance. One of the

most effective is that of the of the salary cap (Fort & Quirk, 1995). The salary cap creates a limit to the total salaries a team can pay its players in a given season. This, in theory, prevents any one team from hoarding the top talent and skewing the league's balance. Additionally, in the NBA, there is also a minimum team salary (90% of the salary cap in the 2014-2015 season), which in theory works in the reverse of the salary cap, preventing a team from being uncompetitive to the point of skewing league balance. Despite this, the NBA has seen one of the higher levels of imbalance in the major sports leagues over the past two decades. Zimbalist (2002) suggests that one such source of imbalance – the Chicago Bulls' dynasties in the 90s – were in part due to the way the league allows teams to go over the salary cap to resign their own players, known as the Bird Exception, allowing the Bulls to retain Michael Jordan more easily. This Bird Exception, named after Larry Bird, allows a team to "re-sign its own free agent to a first-year salary of up to the maximum player salary if he played for the team for some or all of each of the prior three consecutive seasons" even if this would put the team over the salary cap (National Basketball Association, 2014, p. 5). He supports this by pointing out that seven of the top eleven players in the 1997-1998 season were all still playing for the teams they had started their careers with, which would indicate the teams' abilities to resign their own talent. If anything this can be viewed as the exception that proves the rule that the salary cap does in fact hold sway over the balance in the league. By letting the teams skirt around the salary cap, their actions could potentially cause a shift in the competitive balance that may favor them. Though it would then stand to reason that any other team conducting any similar action could cause a shift in the balance as well, which may either further polarize the league, or bring it back closer to balance.

Can this player retention lead to the much desired competitive advantage? Does a team's ability to keep people around actually lead to discernable success? Many examples of such

success exist such as the case of the Chicago Bulls with Michael Jordan and more recently the San Antonio Spurs with Tim Duncan. According to Berman et al. (2002) there is in fact a source of competitive advantage found from keeping a group of players together for an extended amount of time. Looking at the NBA from the 1980-81 season to the 1993-94 season, they found that the longer teammates played together they gained increased levels of team tacit knowledge, which would in turn allow them to perform better. Group tacit knowledge, according to them, is a sort of common knowledge gained as a group has increased experience working together. It allows them to perform more cohesively and anticipate the actions of one another, leading to increased performance. Some of this can be taught through plays and practice, but it is largely unexplainable and must come from experience with one another, otherwise it would not be tacit knowledge. Furthermore, this knowledge does not simply exist within the head of a single individual; each player holds a piece of the collective knowledge. This concept of the collective mind is further supported by Weick and Roberts (1993). It is quite like how puzzle pieces fit together: each piece relies on the others to fit together and form the whole. The tacit knowledge the players possess is largely contextual to their current situation and teammates and may not be as effective elsewhere. This socially complex tacit knowledge can be quite a valuable resource when diffused through the organization (Nelson & Winter, 1982; Barney, 1991; Reed & DeFillippi, 1990). Fostering the growth of this team-tacit knowledge to the point of a competitive advantage would be a maximization of a team's internal resources – the player. However, this only works up to a critical-point where the benefits cease to exist given more time. This point of diminishing returns, called "knowledge ossification" by Berman et al. (2002), can be caused by several factors. The team may have been together for a long time and could be suffering from a lack of young talent that can bring new techniques to the group. Additionally the players could

be hesitant to experiment with new styles of playing as they may be reliant on what they have been doing for so long. Players can also become complacent with their roles on their team and their performance can decline as a result. Finally, other teams in the league may start to learn to play better against the team, especially if they fail to adapt as mentioned above.

While keeping the team together for a long time can be important to gain this tacit knowledge, it may be beneficial to restructure the team and bring in new players every so often as well, despite the paradoxical nature of the idea. Keeping the team together promotes tacit knowledge, but the team misses out on any new entrants who could help the team improve. Adjusting the team's player personnel, however, runs the risk of delaying the growth of the team tacit knowledge. As such, what should we expect when a team brings in resources – players – from outside of the team? Many studies examined coaching changes in sports teams, which can be instructive for attempts to understand the effect of player trades. In one specific study looking at coaching changes in Major League Baseball from 1920 to 1973, Allen, Panian, and Lotz (1979) found that outside, mid-season, and multiple coaching successions typically resulted in lowered team performance, while internal succession, such as an assistant coach replacing the fired head coach, was more successful. This all began with Grusky (1963) who hypothesized that increased amounts of administrative succession in professional baseball teams – in situations which the team manager was fired and subsequently replaced with a new one – had a negative correlation with team performance. As such, a team that was performing poorly would seek to change its coach, which would then cause the team to continue to perform poorly, leading to what Grusky referred to as the vicious-cycle (Grusky 1963). Gamson and Scotch (1964) argued with Grusky's findings and proposed that, in relation to the team management,

coaches had little overall impact on team performance. They came up with three total theories about how coaching succession worked, which are as follows:

> *The common-sense one-way causality theory*. – This explanation fully accepts the fact that the field manager of a baseball team is a major influence on a team's performance. When the team is performing poorly he is rightfully held responsible. Consequently he is fired and replaced with an alternative manager who, it is hoped, will do better. A new manager typically will raise the performance of a team, since he can benefit by avoiding errors that his predecessor made (p. 69).

In this school of thought, we would believe that the team's performance is largely influenced by the abilities of the coach, and as such the team's performance was a reflection of the coach's ability. Thus, if the team was performing poorly, it would mean the coach was also performing poorly. This could be simply be remedied by firing the old coaching and hiring a new one who could improve the team's performance. There is some support of this in the National Hockey League, where White, Persad, and Gee (2007) found that mid-season coaching changes had both a short-term (within the season of the coaching change) and long-term (the following season) positive impact on team performance. They looked at the NHL from 1989 to 2003. For each team studied, they recorded the percent of total possible points earned in the season before the turnover, the season of transition prior to the turnover, the season of transition after the turnover, and the season after the turnover. They included a total of fifteen teams that met their requirements of having the outgoing coach with the team the full season before he was replaced and the incoming coach stay with the team the full season after the transition. Fourteen of the fifteen teams were found to have been performing poorly before the transition occurred, and they found that twelve of the fifteen teams to have improved performance after the coaching change, with six teams performing above .500. They found this trend to persist to the following season. Interestingly, this replicates the findings in an earlier study done by McTeer et. al (1995). They looked at the four major North American sports: Major League Baseball (MLB) from 1900-

1989, National Basketball Association (NBA) from 1952-1988, National Football League (NFL) from 1960-1988) and National Hockey League (NHL) from 1938-1988. For all of the leagues, they found that all teams improved within the season of the coaching change after the transition occurred. In the MLB, NFL, and NBA they saw that there was no significant change in performance the season after the coaching change. In the NHL, however, they also found evidence for an extended improvement.

Thus, it seems that the NHL is alone in showing any real improvements following a coaching change. The other major sports seem to follow along with Gamson and Sctoch's (1964) other theories. Their second theory is:

> *The Grusky two-way causality theory*. – Grusky also assumes that the field manager is a major influence on a team's performance. However, the relationship between effectiveness and succession, he argues, is reciprocal rather than one way. It is certainly true that a team performing badly will frequently cause the manager to be fired. However, such managerial changes tend to have a number of interrelated and undesirable consequences. … Clearly, a managerial change by the Grusky theory should produce a further deterioration in performance by an already faltering team (pp. 69-70).

As with the common-sense one-way theory, it places a lot of importance on the coach. However, it views the turnover process to be quite disruptive to the overall performance of the organization. Because of this, the coaching change would actually hurt the team's already poor performance, which will cause the coach to appear to be underperforming, leading to the risk of further coaching changes. This could potentially trap a team in a vicious cycle of coaching changes and poor performance. Studies have found support for Grusky's hypothesis of the negative correlation between coach turnover rate and organizational effectiveness (Eitzen & Yetman, 1972; Allen et al., 1979; Fizel & D'Itri, 1997). However, many have noted that these declines on team performance can be mitigated by having the coaching change occur during the off-season instead of mid-season (Allen et al., 1979; Audus et. al., 2002; Giambatista, 2004).

This suggests that coaching changes can be quite disruptive to team performance. Off-season changes would be more beneficial in this case, as it would allow the teams more time to adjust to any changes that the coach would bring along, instead of having to face these differences rather abruptly while still competing mid-season.

Finally we get to Gamson and Scotch's (1964) final remaining theory:

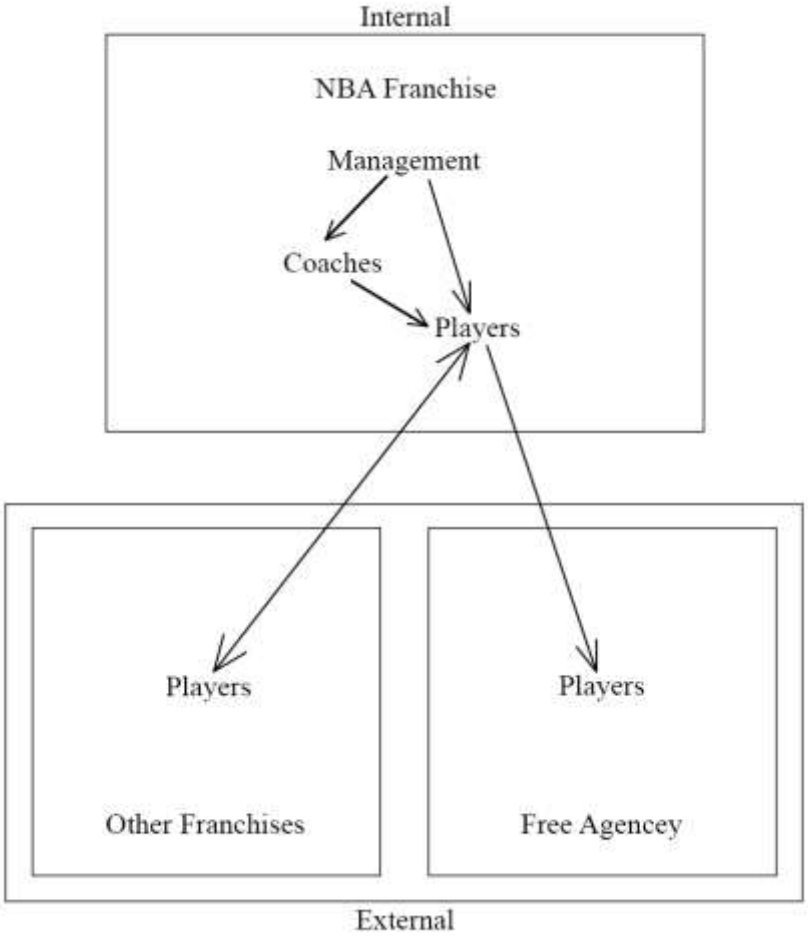
> *The ritual scapegoating no-way causality theory*. – Unlike the above theories, this one assumes the effect of the field manager on team performance is relatively unimportant. In the long run, the policies of the general manager and other front-office personnel are far more important (p. 70).

This theory differs from the other two in that it does not believe the coach is all that important in the grand scheme of things. As it suggests, the front-office may indeed have more broad control over the team than the coach which would make him ineffective in regards to any large-scale changes. On the other end of the spectrum, this theory would place much more importance on the players for the performance of the team, leaving one to believe that there would be no real difference between any qualified individual who was placed in charge of coaching the team. While some studies have seen slight changes in team performance immediately following the coaching change, they end up finding out that in the long-term there is no real difference in team performance. Audus et al. (2006), for example, looked at the National Hockey League and found that when a team would change their coach mid-season they tended to perform worse in the subsequent matches, though they showed this to be short lived. McTeer et al. (1995) on the other hand found there to be some increases in performance following a change in the four major North American leagues, citing the ability of a new manager to re-invigorate the poor performing teams. However, they noted that the improvement did not last long in the MLB, NBA, and NFL. Finally, Brown (1982) was most supportive of the scapegoat theory, finding little evidence of an effect on teams due to coaching succession in the NFL.

While White, Persad, and Gee (2007) and McTeer et al. (1995) have some evidence for improvement following a coaching succession, the other studies failed to find the same. What is interesting about this is that both of these improvements were found in the NHL. As such, is it the nature of the sport that lends it to this phenomenon being seen, or is this just coincidental? Hockey does seem to lend itself to more coaching influence. Coaches will have to adjust a team's shifts (groups of skaters on the ice at one time) to fit their opponents and carefully manage shift changes (substitutions during play) since skaters are typically on ice for around forty seconds at a time. Compare this to basketball where the bulk of a team's minutes are typically split among six to ten players. Given this higher level of player management involved in coaching hockey, it seems reasonable that replacing a poor-performing coach could have a positive impact on performance. However, this is merely speculative and to truly discover the source of these differences would require further research. Additionally, not everyone held the same views on the success of coaching changes in the NHL, as shown by Audus et al. (2006) finding the teams to perform worse shortly after a change.

Since we have seen the effects of building tacit knowledge by keeping the players on a team together for an extended period, and we have an understanding at what happens to a team following coaching turnover, what might be expected from player turnover? Surely if it is possible to achieve competitive advantage from a team's internal resources, there would be reason to believe that it could be possible from outside opportunities. Referring to the diagram below, this would be from trading players with other teams in the league, or by utilizing the free agency via waivers and/or signings.

Figure 3: Internal and External Resources of a Basketball Franchise



To make a fair attempt to understand how trading might actually effect team performance in the NBA, there are several questions that need to be answered. 1) Is there any generalizable change in a team's performance following a significant mid-season trade? 2) Is there any generalizable change in a team's performance if they do not have a significant mid-season trade? 3) Is there any significant difference in the performance of the Trade Teams and Non-Trade Teams in any time frame of the season? 4) Are either Trade Teams or Non-Trade Teams more prone to improve, decline, or have no change over the course of the season? 5) Are either Trade Teams or Non-Trade Teams more likely to make or miss the playoffs at the end of the season?

We can take our possible hypotheses for how player trades affect team performance from Gamson and Scotch (1964), as the principles of replacing an important part of the franchise with another person, typically in mid-season, are basically the same. Thus we have: 1) Since a team is likely performing poorly, replacing some of the poor-performing players with others who bring in fresher talent or fit a missing role will improve the team's performance; 2) The problems with the team's performance are not just limited to that of a few players who can be traded away, and as such, bringing in new players mid-season will only exacerbate the problem and lead to a continued/further decline in the team's performance; 3) The players that teams are willing to give up in a mid-season trade are roughly of the same value, if not in a one-to-one manner then in a net-players-traded one (i.e., three role/bench players for one star player), and as such it should have little impact on the team's overall performance.

Method

Data was collected from Basketball-Reference, an online basketball statistical resource. To start, the season totals for every player in the NBA in a given season were gathered. As per Basketball-Reference's notation, any player who played on multiple seasons has an entry in this season totals list for every team they played on and their total for all teams, which lists TOT for their team. To eliminate redundancies in data for any player who appeared on multiple teams, only their TOT data was included. The next step was to determine who the "significant" players were each season. Given the high number of players in a season ($\mu = 473.2$ players) and the number of trades that happen, it was necessary to figure out which players, and trades, were the most important to analyze. However, this would need to be done with as little bias as possible. As such, a rating was created for each year using a player's minutes per game and games played. For each season, the z-score was found for each player's minutes per game and games played (using: $z = \frac{X-\mu}{\sigma}$, where X is the player's minutes per game or games played stat in the given year, μ is the league average for said stat in the given year, and σ is the league standard deviation for said stat in the given year). This gave each player a "zMPG" and "zGP" stat (standing for z-score: Minutes Per Game and z-score Games Played) which indicate how their minutes per game and games played compare to the rest of the league in that particular year, with a score of 0 being at the league average value and positive numbers indicating better than average. The average z-score of a player's minutes per game and games played was taken (AVGz). The cutoff to qualify a player as "significant" was put at AVGz ≥ 0.75. Thus, any player whose average for the z-scores of his minutes per game and games played within a season was at least 0.75 standard deviations greater than the mean was determined to be a significant player. This takes into account players who played a high number of games, but maybe not as high a number of minutes

per game, or vice versa. Though, due to the relatively skewed nature of both of these stats, these numbers were still rather high. This seems to reinforce the notion that the formula has selected important players. Also, anecdotally, the players that did end up qualifying as significant were known to have been important players. From this we merely select the players denoted with TOT and have the traded qualifiers.

The next step was to find out what trades, and thus teams, would need to be looked at given the significant players. Online databanks were used to match the qualifying players who were traded to the teams they were traded from and the teams they were traded to. Typically trades involve players being sent between both teams (sometimes even three teams), though the players that one team is trading away may not qualify as significant players. Nevertheless, any team that either lost or gained a significant player via a trade was included among the test subjects. Additionally, the date of the trade needed to be denoted so that the season split where the trade occurred, and thus the makeup of the team was changed, could be known for the testing. This was repeated for all significant players within a given year. This can be seen in the following table.

Table 1: Players in Study

Season	Total	Qualifiers	Traded Qualifiers
2010-2011	452	125	15
2011-2012	478	122	5
2012-2013	469	128	4
2013-2014	482	131	6
2014-2015	492	124	16
Total	2,373	630	46
Average	474.6	126	9.2

Next, each team's season data was obtained. This was given as a list of every game the team played in that season. For the 2010-2011 season and 2012-2015 seasons this was 82 games (with the exception of the 2012-2013 Boston Celtics and Indiana Pacers who had a game cancelled due to the Boston Marathon bombings), and for the 2011-2012 season it was 66 games due to the lockout shortening the season. The teams' wins and losses were taken from this list, with a 1 indicating a win and a 0 indicating a loss. For the trade teams, their win percentages were taken pre- and post-trade, no matter when the trade occurred. As a side note, however, many of the trades occurred at or very close to the trade deadline, which is the latest point in the season when teams are allowed to trade. Any team that had more than one trade on different dates (N = 8) were excluded from the data testing as it would be too difficult to determine what trade affected the team the most given the overlapping pre- and post-trade periods. Two teams, the 2014-15 Detroit Pistons and 2014-15 Houston Rockets, were withheld from data because, in addition to both taking part in separate trades, the Pistons waived a significant player (Josh Smith) who was later signed by the Rockets. Though not a trade, this excluded the teams due to the subtraction and addition, respectively, of a significant player. A table showing the breakdown of teams over the years is shown in Table 2.

Table 2: Teams in Study

Season	Trade Teams	Non-Trade Teams	Non-Qualifying Teams
2010-2011	14	16	0
2011-2012	8	21	1
2012-2013	5	25	0
2013-2014	9	20	1
2014-2015	11	13	6
Total	47	95	8
Average	9.4	19	1.6

For the remaining qualifying trade teams (N = 47), their pre-trade win percentages (S1), post-trade win percentages (S2), and total season win percentage (Total) were all recorded. Additionally, a two-tailed t-test was conducted for each team in each season to see if there was any statistically significant change in the team's performance across S1 and S2. These results were incorporated into a later Chi-Squared test for all teams investigated over the five year period. This is shown in the table below.

Table 3: Average Team Win Percentages by Season

	Trade Teams			Non-Trade Teams		
Season	S1:	S2:	Total	S1:	S2:	Total
2010-2011	0.520	0.520	0.519	0.480	0.491	0.483
2011-2012	0.468	0.497	0.479	0.513	0.518	0.515
2012-2013	0.429	0.427	0.432	0.511	0.517	0.514
2013-2014	0.403	0.465	0.450	0.531	0.524	0.527
2014-2015	0.504	0.454	0.477	0.524	0.524	0.523
Average	0.475	0.480	0.480	0.512	0.515	0.513

Any team that did not have a trade in the season, or had a trade that was not determined to be significant, was included in the Non-Trade Teams group. For these teams, a season split was made at the trade deadline to allow comparison with the Trade Teams. This also would hopefully mitigate the influence of any non-significant trades as just a natural change in team performance. Again, as with the Trade Teams, their win percentages for S1, S2, and Total were recorded, and a two-tailed t-test was conducted between each team's S1 and S2, with the results being incorporated into the later Chi-Squared test.

Finally, testing was done on the data. T-tests were done to compare the S1 and S2 data for all of the Trade Teams and Non-Trade Teams, both within each group and to compare the separate groups (i.e. testing Trade Teams' S1 and S2, Non-Trade Teams' S1 and S2, comparing averages of both groups, and comparing the S1 and S2 of both groups). Then, a Chi-Squared test

was constructed using the data collected from the individual t-tests of each team. This compared the rates of Improvement, No Change, and Decline for both the Trade Teams and the Non-Trade Teams, as determined by the individual teams' t-tests mentioned earlier, to see if there was any significant skewedness in how the data was spread out. Another Chi-Squared test was run to determine if the rates of whether a team made or missed the playoffs were different for the Trade Teams and Non-Trade Teams.

Results

Analysis of Trade Team Performance

A paired-samples t-test was used to determine whether there was a statistically significant difference in team performance after a trade as compared to before the trade taking place, while we have the null hypothesis that there is no difference between the two time periods. The performance of these Trade Teams had a slight increase in performance in the S2 timeframe following a trade ($M = .480$, $SD = .180$) as compared to the S1 timeframe before the trade ($M = .475$, $SD = .148$). There was no statistically significant increase in team performance after the trade deadline as compared to before the trade deadline, $M= .005$, 95% CI [-.038, .048], $t(46) = .243$, $p = .809$. Therefore, we fail to reject the null hypothesis as it appears that there is no difference in team performance after a significant trade takes place.

Analysis of Non-Trade Team Performance

A paired-samples t-test was used to determine whether there was a statistically significant difference in team performance for teams without a significant trade after the trade deadline as compared to before the trade deadline, with the null hypothesis that there is no difference between the two time periods. The performance of these Non-Trade Teams saw a slight increase between the S1 timeframe before the trade deadline ($M = .512$, $SD = .168$) and the S2 timeframe after the trade deadline ($M = .515$, $SD = .179$). As such, there was no statistically significant increase in team performance after the trade deadline as compared to before the trade deadline, $M = .003$, 95% CI [-.023, .029], $t(94) = .241$, $p = .810$. Therefore, we again fail to reject the null hypothesis as it appears that there is no natural change in team performance over the course of a season.

Table 4: Paired Samples T-Tests Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Trade Teams S1	0.4753	47	0.14785	0.02157
	Trade Teams S2	0.4804	47	0.17978	0.02622
Pair 2	Non-Trade Teams S1	0.5120	95	0.16793	0.01723
	Non-Trade Teams S2	0.5152	95	0.17882	0.01835

Table 5: Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	Trade S1 & Trade S2	47	0.620	0.000
Pair 2	Non-Trade S1 & Non-Trade S2	95	0.735	0.000

Table 6: Paired Samples Tests

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	Trade S2 - Trade S1	0.00516	0.14562	0.02124	-0.03760	0.04791	0.243	46	0.809
Pair 2	Non-Trade S2 - Non-Trade S1	0.00313	0.12654	0.01298	-0.02264	0.02891	0.241	94	0.810

Comparison of Trade Teams to Non-Trade Teams

S1 Comparison.

There were 47 Trade Teams and 95 Non-Trade Teams. An independent-samples t-test was run to determine if there were differences in the S1 win percentages between Trade Teams and Non-Trade Teams, with the null hypothesis of there being no difference between the two groups. There were no outliers, as determined by inspection of a boxplot. The S1 win percentages were normally distributed, as assessed by Shapiro-Wilk's test ($p > .05$), and there was homogeneity of variances, as assessed by Levene's test for equality of variances ($p = .277$). The Non-Trade Teams performed better in their respective S1 timeframes ($M = .512$, $SD = .168$) than did the Trade Teams ($M = .475$, $SD = .148$). There was no statistically significant difference in the mean S1 win percentage between Trade Teams and Non-Trade Teams, with Trade Teams performing only slightly worse than the Non-Trade Teams, $M = -.037$, 95% CI [-.094, .020], $t(140) = -1.275$, $p = .205$.

S2 Comparison.

An independent-samples t-test was run to determine if there were differences in the S2 win percentages between Trade Teams and Non-Trade Teams, with the null hypothesis of there being no difference between the two groups. There were no outliers, as determined by inspection of a boxplot. The S2 win percentages were normally distributed, as assessed by Shapiro-Wilk's test ($p > .05$), and there was homogeneity of variances, as assessed by Levene's test for equality of variances ($p = .618$). The Non-Trade Teams again performed better in their respective S2 timeframes ($M = .515$, $SD = .179$) than did the Trade Teams ($M = .480$, $SD = .180$). There was no statistically significant difference in the mean S2 win percentage between Trade Teams and

Non-Trade Teams, with Trade Teams performing only slightly worse than the Non-Trade Teams, M = -.035, 95% CI [-.098, .028], t(140) = -1.087, p = .279.

Total Comparison.

An independent-samples t-test was run to determine if there were differences in the overall season win percentages between Trade Teams and Non-Trade Teams, with the null hypothesis of there being no difference between the two groups. There were no outliers, as determined by inspection of a boxplot. The Total win percentages were normally distributed, as assessed by Shapiro-Wilk's test (p > .05), and there was homogeneity of variance, as assessed by Levene's test of equality of variances (p = .335). The Non-Trade Teams once again performed better (M = .513, SD = .161) than the Trade Teams (M = .480, SD = .146). There was no statistically significant difference in the mean Total win percentage between the Trade Teams and Non-Trade Teams, with Trade Teams performing only slightly worse than the Non-Trade Teams, M = -.033, 95% CI [-.088, .022], t(140) = -1.193, p = .235.

Table 7: Group Comparison T-Tests Statistics

Team		N	Mean	Std. Deviation	Std. Error Mean
S1	Trade	47	0.4753	0.14785	0.02157
	Non-Trade	95	0.5120	0.16793	0.01723
S2	Trade	47	0.4804	0.17978	0.02622
	Non-Trade	95	0.5152	0.17882	0.01835
Total	Trade	47	0.4798	0.14580	0.02127
	Non-Trade	95	0.5131	0.16128	0.01655

Table 8: Group Comparison Tests of Normality

Team		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
S1	Trade	0.066	47	.200*	0.979	47	0.568
	Non-Trade	0.063	95	.200*	0.981	95	0.172
S2	Trade	0.110	47	0.197	0.963	47	0.146
	Non-Trade	0.066	95	.200*	0.991	95	0.774
Total	Trade	0.106	47	.200*	0.970	47	0.259
	Non-Trade	0.084	95	0.094	0.974	95	0.057

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Table 9: Group Comparison Independent Samples Tests

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
S1	Equal variances assumed	1.190	0.277	-1.275	140	0.205	-0.03674	0.02882	-0.09372	0.02024
	Equal variances not assumed			-1.331	102.934	0.186	-0.03674	0.02760	-0.09148	0.01801
S2	Equal variances assumed	0.250	0.618	-1.087	140	0.279	-0.03472	0.03195	-0.09787	0.02844
	Equal variances not assumed			-1.085	91.341	0.281	-0.03472	0.03200	-0.09828	0.02885
Total	Equal variances assumed	0.936	0.335	-1.193	140	0.235	-0.03327	0.02788	-0.08840	0.02186
	Equal variances not assumed			-1.235	100.524	0.220	-0.03327	0.02695	-0.08673	0.02018

Chi-Squared Comparison of Types of Change in Trade and Non-Trade Teams

A chi-squared test for association was conducted between the Trade Teams and Non-Trade Teams and whether the teams improved, declined, or had no change between the given time periods, with the null hypothesis that there was no relationship. Three of the cells had expected values less than five, with the minimum expected count being 1.99. There was no statistically significant association between whether a team had a mid-season trade or not and the change in their performance over the season, χ^2 (2) = 1.255, p = .534.

Table 10: Team * Change Crosstabulation

			Change			
			Decline	Improve	NoChange	Total
Team	Non-Trade	Count	5	5	85	95
		Expected Count	4.0	6.0	85.0	95.0
	Trade	Count	1	4	42	47
		Expected Count	2.0	3.0	42.0	47.0
Total		Count	6	9	127	142
		Expected Count	6.0	9.0	127.0	142.0

Table 11: Team * Change Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	1.255[a]	2	0.534
Likelihood Ratio	1.324	2	0.516
N of Valid Cases	142		

a. 3 cells (50.0%) have expected count less than 5. The minimum expected count is 1.99.

Table 12: Team * Change Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	0.094	0.534
	Cramer's V	0.094	0.534
N of Valid Cases		142	

Chi-Squared Comparison of Playoff Appearances

A chi-squared test for association was conducted between the Trade Teams and Non-Trade Teams and whether the teams made playoffs or not, with the null hypothesis of there being no relationship. All expected cell frequencies were greater than five. There was no statistically significant association between whether a team had a mid-season trade or not and whether the team made playoffs or not, χ^2 (1) = .792, p = .374.

Table 13: Team * Playoffs Crosstabulation

			Playoffs		
			Made	Missed	Total
Team	Non-Trade	Count	54	41	95
		Expected Count	51.5	43.5	95.0
	Trade	Count	23	24	47
		Expected Count	25.5	21.5	47.0
Total		Count	77	65	142
		Expected Count	77.0	65.0	142.0

Table 14: Team * Playoffs Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.792[a]	1	0.374		
Continuity Correction[b]	0.505	1	0.477		
Likelihood Ratio	0.791	1	0.374		
Fisher's Exact Test				0.474	0.238
N of Valid Cases	142				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 21.51.

b. Computed only for a 2x2 table

Table 15: Team * Playoffs Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	0.075	0.374
	Cramer's V	0.075	0.374
N of Valid Cases		142	

Discussion

Trade Team Performance

The increase across the time periods was so miniscule that both S1 and S2 would, on average, have proportionally the same amount of wins. For example, if extrapolated to 82 games, as in a full NBA season, the S1 average record would net a team 38.95, while the S2 average record would net a team 39.36. Since a team cannot have a win value that is not a whole number, we should round both of these to 39 wins, further establishing there being no real difference. It may be worth noting that the spread of values is a bit wider in S2 as compared to S1. In S1, the win percentages located within ±1 standard deviation range from .327 to .623. Again, transposing these win percentages to 82 games, this would be akin to a range of 26.81 wins to 51.09 wins (or more appropriately, 27 to 51 wins). Meanwhile, in S2, the win percentages located within ±1 standard deviation range from .300 to .660. Putting this in terms of an 82 game season, this would be like a range of wins from 24.6 wins to 54.12 (rounding this would be a range of 25 wins to 54 wins). Thus you can see that the range of wins where we can expect 68% of teams to fall has increased by five (two on the low end and three on the high end). Granted, the true win values in S1 and S2 will be more condensed since each only represents a portion of the full season, but it is still interesting to note that there is a higher spread in S2, leading to the conclusion that there is no generalizable outcome.

Since this study indicates that these mid-season trades have no generalizable effect on team performance, it supports the theory that the players exchanged in a trade all end up being relatively the same, echoing support for the Scapegoat theory proposed by Gamson and Scotch (1964). Additionally, although Berman et al. (2002) found that keeping a team together for an extended period of time leads to an improvement in team performance to the point of it

becoming a competitive advantage, which seems to indicate that any disruptions, such as a mid-season trade of an important player, would hurt this growth, the results of this study indicate that this might not be the case. Similarly, it does not outright support their supposition in their discussion that obtaining new, better players might improve team performance, though this is largely due to the design of my own study. Indeed, further investigations about the teams, especially the ones that traded and saw a statistically significant increase in performance, may shed more light on this possibility.

Additionally, the fact that the Trade Teams were, on average, below .500 before trading brings back a common theme from the literature on coaching succession: change happens when a team is performing poorly. This was most specifically expressed in the works of Allen et al. (1979) and White et al. (2007) looking at coaching succession. It may be of worth to see if the occurrence of one form of succession can predict the other happening, or if some combination of the two might lend itself to greater levels of improvement or decline in team performance.

One of the interesting finds when looking at the individual seasons was that three of the four teams that improved after a trade were all in the 2013-14 season. Another curious fact was that three of the four teams who traded and improved actually traded away a significant player without getting one back in return. These teams were the 2013-14 Chicago Bulls, the 2013-14 Toronto Raptors, and the 2014-15 Utah Jazz. As a counterpoint, the 2014-15 Oklahoma City Thunder received three significant players and seemed to have their performance increase. However since they also had multiple significant trades in the season, their data was excluded.

Non-Trade Team Performance

The S1 and S2 data for the Non-Trade Teams are very similar here. Once again, the difference in the average win percentage in both the pre-trade-deadline (S1) and post-trade-

deadline (S2) groups is so small it is virtually negligible. Moreover, the changes in standard deviation are smaller than that seen in the Trade Teams. This seems to support the notion that there is not much of a natural change in team performance over the course of the season, which also leads me to believe it was an appropriate control group.

It would also seem worthwhile to further study the Non-Trade Teams, particularly the five that improved and the five that declined over the course of the season. This could determine what caused these teams to change in performance when there was no apparent drastic change in the team, or point out any confounding variable that may have been ignored in this study due to its design, such as a trade not determined to be significant, a coaching change, or an injury to an important player. One particularly salient case is that of the 2012-13 San Antonio Spurs and Miami Heat. These two teams met in the NBA Finals that season. What is interesting here is that both of these teams were determined to have a significant change in their performance from the part of the season before the trade deadline to the part after. The Miami Heat, who won the Championship, were determined to have improved between these two time periods. The San Antonio Spurs, who lost, were determined to have declined between these two time periods. This was the only case of a team that had a statistically significant change in performance making the NBA Finals, let alone two of them.

Comparison of Trade Teams to Non-Trade Teams

S1 Comparison.

This testing showed that the two groups are, on average, not statistically different in their initial time frame. However, it is worthwhile to note that the Trade Teams were on average below .500, while the Non-Trade Teams were above .500. Again, since these were not determined to be statistically significantly different, we cannot make generalizations about any

differences in the two groups. On the other hand, any basketball fan would be able to tell you there is a difference between a team below .500 and one above .500. Interestingly, there was a wider spread in Non-Trade Teams than the Trade Teams.

S2 Comparison.

This is the comparison between the latter time frames for each group. Again we see that, despite an observable difference between the two groups, it was determined that they were not statistically significant enough. So, as with the S1 comparisons, while we can say that, from a basketball perspective, there appears to be a difference between the performance of the Trade Teams and Non-Trade Teams, statistically it is not large enough to draw any real conclusions.

Total Comparison.

Here we looked to see if the overall, end-of-season win percentages of the Trade Teams and Non-Trade Teams were statistically significantly different. As with the other two comparisons between the two groups' performances, we have an observable difference that is determined to not be statistically significantly different. Here we see that the Trade Teams average out at 39.36 wins in a season, while the Non-Trade Teams average out at 44.53 wins. Rounding these we would get Trade Teams at 39 wins and Non-Trade Teams at 45 wins, a difference of 6 wins. This very well could be a tangible difference in the NBA, but given the results of the statistical testing, we again cannot say they are significantly different enough.

Chi-Squared Comparison of Types of Change in Trade and Non-Trade Teams

Here we looked to see if the occurrence of whether a team improved, declined, or had no change in performance from S1 to S2 was tied to whether they had a trade or not. While both groups on average had no change in performance, both groups did have a number of subjects that did see a statistically significant change in their performance. Because of this it was important to

see if one group was more likely to improve or decline or have no change when compared to the other. However, as the test statistics showed, the groups were determined to be even. While there were a few groups with expected values less than five, this does not seem to be an issue due to the overall sample size and the previously established notion that teams in both groups will, on average, see no change in performance.

Chi-Squared Comparison of Playoff Appearances

In this final test, we looked to see whether there was a difference in the rate at which Trade Teams and Non-Trade Teams made or missed the playoffs at the end of a season. Since there is a distinction between a team that makes the playoffs and one that does not, it would be worthwhile to see if one group was more likely to make or miss the playoffs than the other. Once again, our test-statistics showed that this was not the case; rather the two groups were evenly distributed among the two possibilities.

Conclusion

The results of this research create a number of new questions for future scholars. First, why are the teams performing the way they are after a trade? If we could figure out why some trades result in improved performance while others result in declined performance we could strive to only engaging in trades that would be beneficial for the team. Additionally, it would be worth noting if any of these teams that show a decline in performance post-trade were attempting to engage in what is commonly referred to as “tanking” in an attempt to secure a top draft-pick. If this were the case, then this could be viewed as a success of sorts. On the other side of this study, it would be worthwhile to look at some of the non-trade teams to see if there was any way to figure out how the few teams that improved in the second half of the season did so, or why the teams that declined did so.

Another change that could be made in the future could be the traded-players, and thus the trades, that are looked at. Nevertheless, I feel that the definition of a significant player that was established is a satisfactory one. However, others may want to broaden future studies. As with anything else, more data could lead to more accurate results.

In the end, the results of this study suggest that a mid-season trade does not have a significant impact on team performance. Since this looked at any differences that were *statistically significant* it does overlook some minor differences. For instance: the overall records of the Trade Teams, averaging at .480, and Non-Trade Teams, averaging at .513, were deemed to not be *statistically significantly* different, from the eyes of a basketball enthusiast, there would seem to be a difference there indeed. However, since this could likely be accounted to below-.500 teams being more likely to trade than over-.500 teams. Again, since there were no differences either within the two groups or between them it leads one to believe anything is off. As such the findings can be summed up as follows: Trades do not seem to hurt a team, nor do they seem to help either. This is especially interesting since much of the previous literature and studies discussed would seem to indicate that a trade would be detrimental. If keeping a team core together for an extended period is typically beneficial, then it should be expected that a disruption to that process, like a trade, would be detrimental to performance. Similarly, if mid-season coaching changes tend to hurt team performance, one might think that the players, who more directly impact a game's outcome, would have a similar impact when traded mid-season. However, this does not seem to be the case at this point in time. Indeed it seems that there are a complex system of interactions that govern team performance, both within a team running between the management, coaches, and players, and between the team and its environment.

Continued investigation into these relationships – how they work and how changes to one part affect another – is imperative to the continued growth of the manager and the field as a whole.

Bibliography

Audas, R., Dobson, S., & Goddard, J. (2002). The impact of managerial change on team performance in professional sports. Journal of Economics and Business, 54, 633–650.

Audas, R., Goddard, J., & Rowe, W. G. (2006). Modelling Employment Durations of NHL Head Coaches: Turnover and Post-Succession Performance. Managerial and Decision Econoics, 27(4), 293–306.

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. Journal of Management, 17(1), 99–120.

Barney, J. B. (2001). Is the Resource-Based "View" a Useful Perspective for Strategic Management Research? Yes. The Academy of Management Review, 26(1), 41–56.

Brown, C. (1982). Administrative Succession and Organizational Performance: The Succession Effect. Administrative Science Quarterly, 27(1), 1–16.

CBA 101 Highlights of the 2011 Collective Bargaining Agreement Between the National Basketball Association (NBA) and the National Basketball Association (NBPA). (2014, September). NBA.

Christensen, C. R., Andrews, K. R., & Bower, J. L. (1978). Business Policy Text and Cases (Fourth Edition). Richard D. Irwin, Inc.

Dosi, G., Teece, D. J., & Chytry, J. (Eds.). (1998). Technology, Organization, and the Firm. New York: Oxford University Press.

Eitzen, D. S., & Yetman, N. R. (1972). Managerial Change, Longevity, and Organizational Effectiveness. Administrative Science Quarterly, 17(1), 110–116.

Fizel, J. L., & D'Itri, M. P. (1997). Managerial Efficiency, Managerial Succession and Organizational Performance. Managerial and Decision Economics, 18(4), 295–308.

Fort, R., & Quirk, J. (1995). Cross-Subsidization, Incentives, and Outcomes in Professional Team Sports Leagues. Journal of Sports Economics, 33(3), 1265–1299.

Gamson, W. A., & Scotch, N. A. (1964). Scapegoating in Baseball. American Journal of Sociology, 70(1), 69–72.

Giambatista, R. C. (2004). Jumping through hoops: A longitudinal study of leader life cycles in the NBA. The Leadership Quarterly, 15, 607–624.

Grusky, O. (1963). Managerial Succession and Organizational Effectiveness. The American Journal of Sociology, 69(1), 21–31.

Hofer, C. W., & Schendel, D. (1978). Strategy Formulation: Analytical Concepts. West Publishing Company.

Humphreys, B. R. (2002). Alternative Measures of Competitive Balance in Sports Leagues. Journal of Sports Economics, 3(2), 133–148.

Késenne, S. (2000). Revenue Sharing and Competitive Balance in Professional Team Sports. Journal of Sports Economics, 1(1), 56–65.

McTeer, W., & White, P. G. (1995). Manager/coach mid-season replacement and team performance in professional team sport. Journal of Sport Behavior, 18(1), 58–68.

Pfeffer, J., & Davis-Blake, A. (1986). Administrative Succession and Organizational Performance: How Administrator Experience Mediates the Succession Effect. The Academy of Management Journal, 29(1), 72–83.

Porter, M. E. (1980). Competitive Strategy. New York, NY: The Free Press.

Porter, M. E. (1981). The Contributions of Industrial Organization To Strategic Management. The Academy of Management Review, 6(4), 609–620.

Porter, M. E. (1985). Competitive Advantage. New York, NY: The Free Press.

White, P., Persad, S., & Gee, C. J. (2007). The Effect of Mid-Season Coach Turnover on Team Performance: The Case of the National Hockey League (1989-2003). International Journal of Sports Science & Coaching, 2(2), 143–152.

Zimbalist, A. S. (2002). Competitive Balance in Sports Leagues. Journal of Sports Economics, 3(2), 111–121.